DEVELOPMENT OF A FATIGUE TESTING MACHINE USING A PNEUMATIC ARTIFICIAL MUSCLE

Juan Gerardo Castillo Alva
Eleazar Cristian Mejia Sanchez
Marco Antonio Meggiolaro
Jaime Tupiassú Pinho de Castro
Pontifical Catholic University of Rio de Janeiro, Department of Mechanical Engineering
Rua Marquês de São Vicente 225, Gávea. Rio de Janeiro, RJ – 22543-900
gcastillo@aluno.puc-rio.br
cris_ms@aluno.puc-rio.br
meggi@puc-rio.br
jcastro@puc-rio.br

Abstract. Over the years, different kinds of fatigue testing machines have been developed by researchers, actuated by mechanical, electrical, pneumatic or electromagnetic mechanisms. In recent years, there has been an increase in demand for a compact testing machine. Pneumatic systems are an alternative to the traditional servo-hydraulic machines whenever the forces required are not very high. In this work, a pneumatic system to perform fatigue testing is developed, employing inexpensive elements. A pneumatic artificial muscle with a 4kN load capacity is coupled with pneumatic valves to generate variable amplitude loads. A control system has been developed particularly for this machine, using learning control techniques to maximize the velocity of the test without compromising its accuracy. The proposed methodology consists on implementing a bang-bang control type to restrict the solenoid valve to permanently work at its extreme operation limits, always completely open in either one or other direction. The inputs for both algorithms are the range (twice the amplitude) and minimum component of each load event to be applied to the test specimen. Both the learning and the neuro-fuzzy learning algorithms studied in this work try to obtain the optimal instants for the servo-valve reversions, associating them to a non-dimensional variable with values between 0 and 1. The learning algorithm uses a table to store the non-dimensional variables associated with each range-minimum combination. The table values are constantly updated by the learning laws during the test execution, improving the system response. The neuro-fuzzy techniques, on the other hand, do not need these tables, decreasing the memory requirements of the computational system. The range and minimum values of each loading event are entered into the neuro-fuzzy system, which then calculates the instant of servo-valve reversion. The learning process is done by updating the weights of the neuro-fuzzy system, based on the measured errors during the tests, gradually improving the system response. The control methods are implemented in a real time control software running in a CompactRio computational system. It is shown that it is possible to develop a compact fatigue testing machine, easy to handle and transport, which does not require a complex control system, at an affordable cost.

Keywords: fatigue machine; pneumatic artificial muscle; learning control; bang-bang control; neuro-fuzzy control.

1. INTRODUCTION

Fatigue is a type of mechanical failure caused by repeated application of variable loads, whose main characteristic is the generation and/or propagation of a crack gradually until the eventual fracture of the piece. The terminal event of fatigue cracks is the fracture, rupture or breakage of a structure into two or more parts, when it reaches the maximum load (Meggiolaro, M.A., 2009). Fatigue testing machines are intended to test material specimens to predict their service lives. These testing machines are generally based on servo-hydraulic systems, where the forces applied can be very high. For small load capacity systems, the use of compressed gas can be an alternative solution. In a fatigue test, the loads applied to the test specimens are due to the cross-sectional area of the specimen, therefore you can work with smaller bodies, obtaining the same results on the test. Size effects may be present in the crack initiation test under begin or torsion caused by differences in stress gradient, but for tensile-compressive these effects are usually disregarded. Working with samples of smaller dimensions enables the possibility to build a small machine for fatigue tests. In this work is modeling the control system of pneumatic machine, a computer simulation system for variable and constant amplitude load, and the application of control techniques for learning and neuro-fuzzy learning control. The experimental verification was done in pneumatic machine built for fatigue tests in the fatigue laboratory at PUC-Rio University especially for this work, from a pneumatic artificial muscle of 4kN load capacity driven by a pneumatic solenoid valve for generating variable amplitude loading.

2. PNEUMATIC SYSTEM MODELING

The pneumatic muscle is an actuator which converts pneumatic energy into mechanical energy, transferring the pressure applied to the muscle into the inner surface of his bladder into mechanical force. There are different models aimed at solving the pneumatic muscle dynamic, a specific model for the muscle strength is developed below, which depends on the damping, stiffness, pressure (p) and the muscle contraction (ε):

$$F_{muscle}(\varepsilon, \dot{\varepsilon}, p) = F_{spring}(\varepsilon, p) + F_{damping}(\dot{\varepsilon}, p) \tag{1}$$

The damping component of the muscle force is calculated on the same way that the mechanical damping, proportional to the speed $F_{damping} = -c.v$. In this case, the damping constant c is a function of the pressure $c = f(C_D, p)$. Thereby the damping component of the muscle force is expressed as a function of the pressure and the speed.

$$F_{damping}(\dot{\varepsilon}, p) = -C_D p\dot{\varepsilon} \tag{2}$$

where C_D is the damping coefficient, p is the pressure and $\varepsilon´$ is the speed.

In order to find the spring component of the muscle force, the virtual work principle is used (Tondu and Lopez, 2000). It should be have a balance of virtual work done by the pressure in the muscle dW_{in} and the virtual work done by the muscle displacement dW_{out} (see Figure 1).
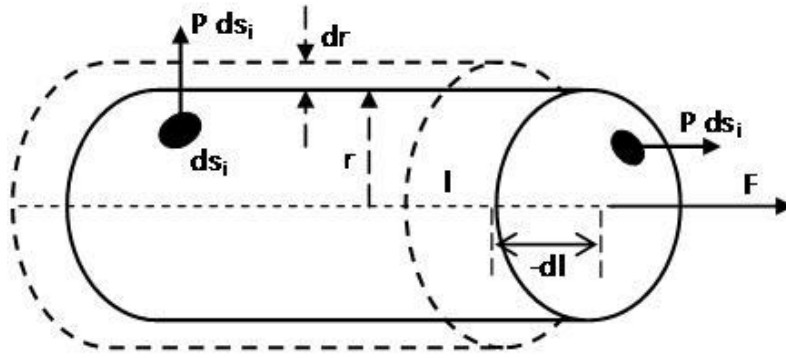

Figure 1. Schematic diagram of two interacting components of virtual works

The input work (W_{in}) done in the pneumatic actuator when the air compressed exerts force on the inner surface of the bladder is defined as:

$$dW_{in} = \int_{S_i} (p - p_0) dl_i dS_i \tag{3}$$

$$dW_{in} = (p - p_0) \int_{S_i} dl_i dS_i = p'dV \tag{4}$$

$$dW_{out} = -Fdl \tag{5}$$

where F is the axial force and dl is the axial displacement.

From the point of view of energy conservation, the input work should be equal to the output work as long as the system has no losses and does not store energy. It is assumed that the actuator is in an ideal condition. You can also use the virtual work concept, then:

$$dW_{out} = dW_{in} \tag{6}$$

Thus, the equation (4) and (5) has:

$$-FdL = P'dV \tag{7}$$

$$F = -P'dV/dL \qquad (8)$$

It is also possible as proposed in (Tondu and Lopez, 1995) to divide the force in one radial and another axial component. The virtual work theorem illustrated in Fig. 1 leads to:

$$dW_{out} = dW_{lateral\_pressure} + dW_{axial\_pressure} \qquad (9)$$

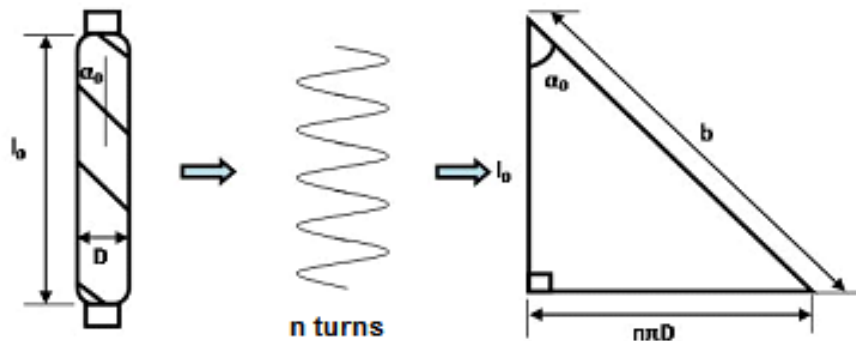$$dW_{out} = (2\pi r l p)dr - (\pi r^2 p)(-dl) = -Fdl \qquad (10)$$

Figure 2. Geometric parameters of the pneumatic artificial muscle

With the help of Figure 2, it can be formulated the correlation between the muscle radius (r), the muscle length (l), and the fiber angle (α_0). Due to the fact that the fibers length is a constant, there are the following relations (Chou, Ching-Ping and Hannaford Blake, 1994) (Daerden F. et al, 2002):

$$l/l_0 = \cos\alpha / \cos\alpha_0 \qquad (11)$$

$$r/r_0 = \sin\alpha / \sin\alpha_0 \qquad (12)$$

Whit these relations one can calculate the correlation between r and l:

$$r = r_0 \left(\frac{\sqrt{1-\cos^2\alpha}}{\sin\alpha_0} \right) = r_0 \left(\frac{\sqrt{1-\left(\dfrac{l}{l_0}\cos\alpha_0\right)^2}}{\sin\alpha_0} \right) \qquad (13)$$

$$F = \pi r_0^2 p \left(\frac{l^2}{l_0^2} \frac{3}{\tan^2\alpha_0} - \frac{1}{\sin^2\alpha_0} \right) \qquad (14)$$

The force F can be expressed as a function of the pressure p and the contraction $k = (l_0 - l)/l_0$:

$$F(p,\varepsilon) = \pi r_0^2 p \left(a(1-\varepsilon)^2 - b \right) \qquad (15)$$

with $a = 3/\tan^2\alpha_0$ and $b = 1/\sin^2\alpha_0$

A disadvantage of this model is that its design is based on the hypothesis of a continuous cylindrical shape of the muscle, whereas in reality it takes a conical shape on both sides while it contracts. Consequently, when the muscle contracts further, it decreases its active part. This phenomenon results from the current ratio of the maximum contraction, theoretically much lower than expected in Eq. (11). To compensate this side effect, a parameter k (k≤1) is considered, which increases the ratio of contraction (ε) by the factor (k). The force generator model modified is:

$$F(p,\varepsilon) = \pi r_0^2 p \left(a \left(1-k\varepsilon\right)^2 - b \right) \qquad 0 \ll \varepsilon \ll \varepsilon_{max} \tag{16}$$

where the factor κ is defined as:

$$k(p) = a_k e^{-p} + b_k \tag{17}$$

where the values a_κ and b_κ are determined experimentally and the maximum relation of contraction is divided by the factor κ:

$$\varepsilon_{max} = \left(1/k\right)\left(\sqrt{1-b/a}\right) \tag{18}$$

Inserted in the static model, the parameter does not change the maximum force value for a given contraction ratio equal to zero. This is in agreement with the experimental part, because the muscle has a cylindrical shape only when contraction is zero. Furthermore, the parameter k allows adapting the ratio of maximum contraction of the model given in the previous equation to the experimental data.

The total force generated by the muscle as defined in equation (1) is:

$$F_{muscle}(\varepsilon,\dot{\varepsilon},p) = \pi r_0^2 p \left(a \left(1-k\varepsilon\right)^2 - b \right) - C_D p\dot{\varepsilon} \tag{19}$$

The system equations representing the solenoid valve can be compactly represented by an equation which represents the mass flow in the valve.

$$\dot{m} = f_v C_a A_v \sqrt{p_0 - p} \tag{20}$$

where the value of f_v=1 or -1 depends on whether the muscle is filling or emptying compressed air, A_v is a valve opening area, C_a is the valve opening constant.

3. CONTROL SYSTEM

In this work, two control techniques were used: learning control and neuro-fuzzy learning control applied in pneumatic system. The goal of both control systems is to find the reversal point of the solenoid valve with which reach the peak and valley desired. Both control systems try to keep the solenoid valve working in only two states, on and off; this type of control is known as Bang-Bang.

3.1 Learning Control

For the learning control, the instant of reversion is represented by an U_{IJ} dimensionless variable, which is defined as a fraction of the path peak-valley or valley-peak where the valve should be switched on or off, depending on the previous state (Alva JGC et al, 2009). For example, when controlling a force cycle of 100 to 1000N, a value of U_{IJ}=0,8 is equivalent to reversing the solenoid valve when exceed 80% of the way between 100 and 1000N, which is equivalent to reverse the solenoid valve "100+0,8·(1000-100)=820N", in the case of returning from 1000 to 100N, the value of reversal would be "1000-0,8·(1000-100)=280N". This U_{IJ} value is a parameter that depends on several factors, such as mean value and amplitude of the loading required, and is influenced in some cases by fixing gaps in the test specimen. The U_{IJ} value is stored in learning tables. The U_{IJ} value is updated according to the error between the peak (or valley) reached (measured) x and the peak or valley desired x_d where x' is a measured valley (or peak, respectively) in the previous reversal, the error is defined by the dimensionless value (Alva J G C et al, 2009):

$$error = \left(x_d - x \right) / \left(x_d - x' \right) \tag{21}$$

Assuming, in general, -1<error<1, we can propose the learning law:

$$U_{IJ} := U_{IJ} \left(1 + error \right) \tag{22}$$

3.2 Neuro-fuzzy Learning Control

The learning process can be viewed as an estimation problem or successive approximations of functions or unknown quantities. In this case, the unknown quantities estimated or learned by the controller are parameters governed by the control laws. In this control model, the information is represented by a U_{IJ} dimensionless variable, which in this case is the output of the neuro-fuzzy system. This variable stores the instant of the solenoid valve should be reversed, and is a number between 0 and 1 (0 for the beginning of the reversal, and 1 for the reverse at the end of course). The information generated by the U_{IJ} value is stored in the weights of the structure of the neuro-fuzzy system (see Figure 3). The U_{IJ} variable used to change the reversion instant of the solenoid valve is updated after each operation cycle by adjusting the weights of the neuro-fuzzy structure, using a learning algorithm based on the measured errors. The purpose of the neuro-fuzzy system is to provide the U_{IJ} value to the controller, thus determining the instant of reversion in which the valve will reverse its direction, so that the machine (pneumatic system) is maintained in its working operation limits (Sanchez E C M et al, 2011).
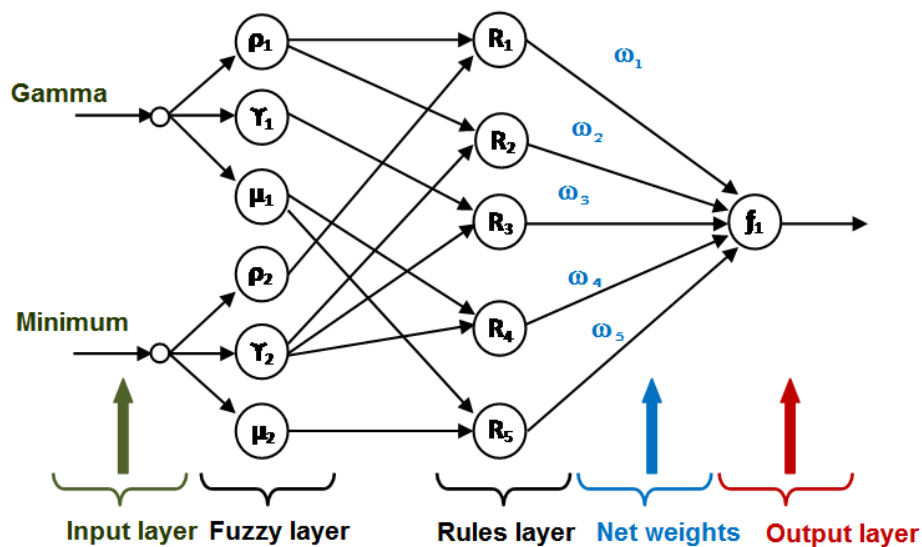

Figure 3. Description of the layers of the neuro-fuzzy system

The instants of reversion of the solenoid valve for the learning control and the neuro-fuzzy learning control are calculated from the value of the U_{IJ} variable.

$$ReversionPoint = \begin{cases} minimun + U_{IJ} gamma & upstream \\ \left(minimum + gamma \right) - U_{IJ} gamma & downstream \end{cases} \tag{23}$$

4. PNEUMATIC SYSTEM SIMULATIONS

Figure 4 shows the simulations for a constant amplitude load of 3500N of peak and 1000N of valley applied to the pneumatic muscle, with an initial U_{IJ} value of 0,60. For this loading, the learning control managed to learn the desired value in about 3 seconds, or 15 load cycles, and the frequency of work achieved for the requested values was 5 Hz. The learning is considered satisfactory when the error value (sum of the absolute value of peak and valley error) is less than 0,01%.
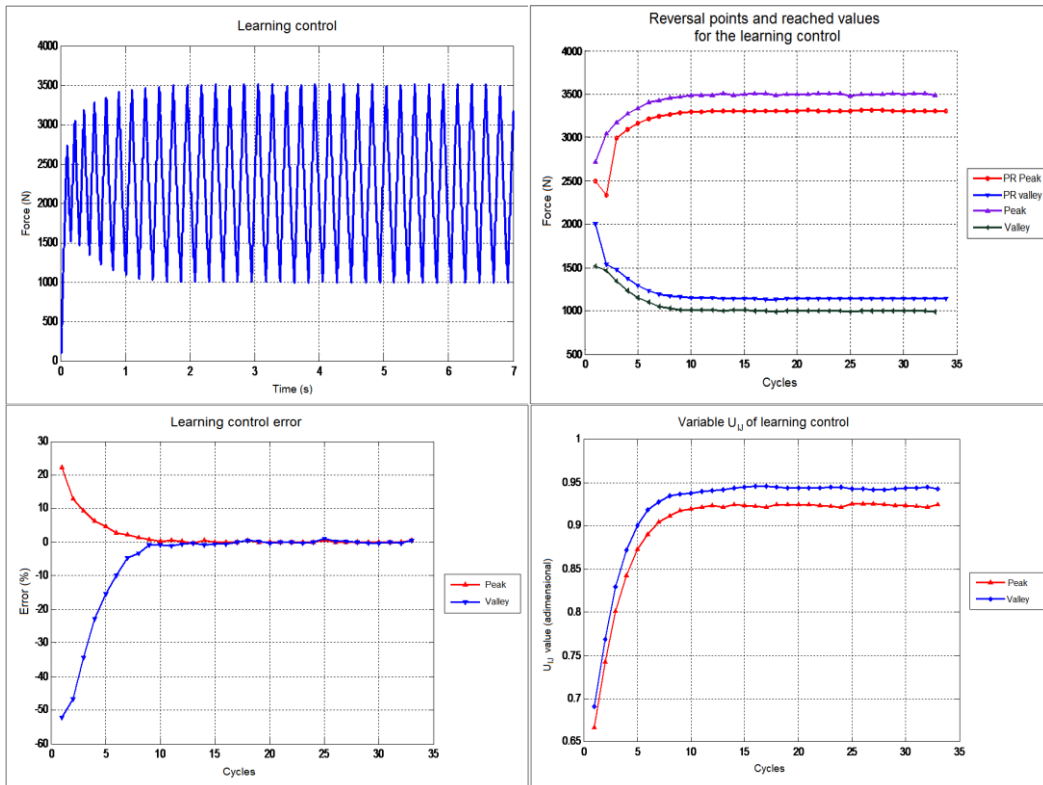
Figure 4. Simulation of learning control for constant amplitude loading {3500-1000}N

In the case of variable amplitude loading, for each pair of loadings requested, variables are learned and stored in the learning array, in this case populating four neighboring elements in concordance with the gamma and the minimum associated to the loading event. The determination to continue or not the learning process depends only on the error level reached; in this work, the relative error considered acceptable in the simulations was 0,01% for all cases. Figure 5 shows the results of the simulation of the behavior of learning control for variable amplitude loading.
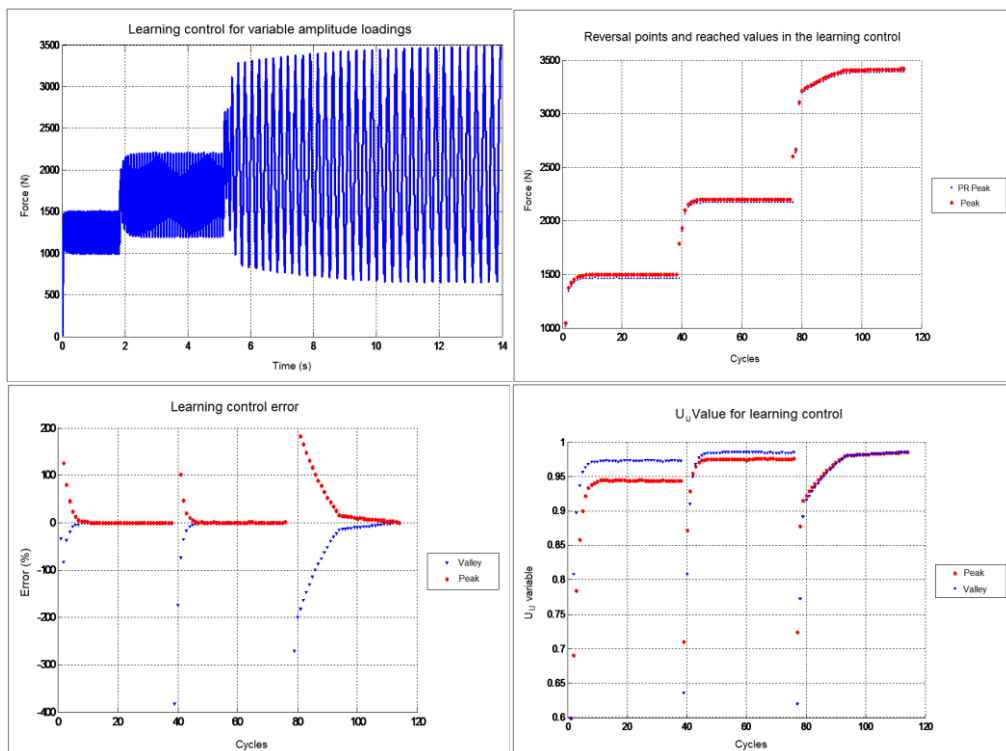
Figure 5. Simulation of learning control for variable amplitude loading {1500-1000-2200-1300-600}N

Figures 6 and 7 show the simulations for different loads of constant amplitude and variable amplitude, and in all cases the U_{IJ} initial value was 0,60 and the learning rate equal to 0,25.
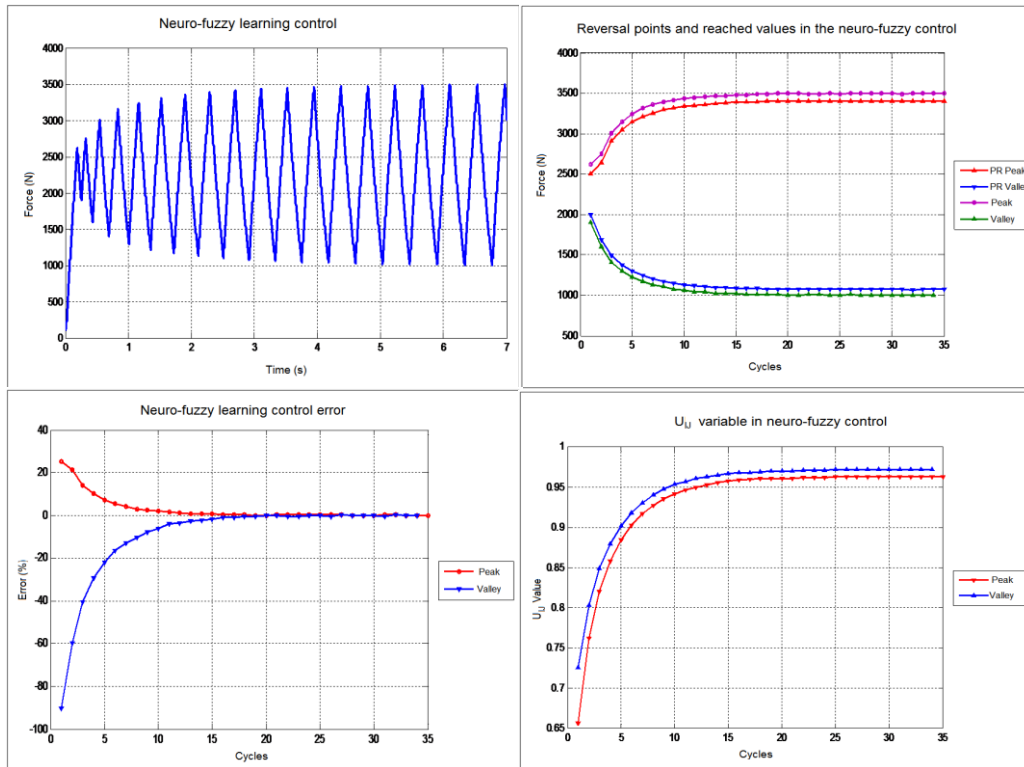

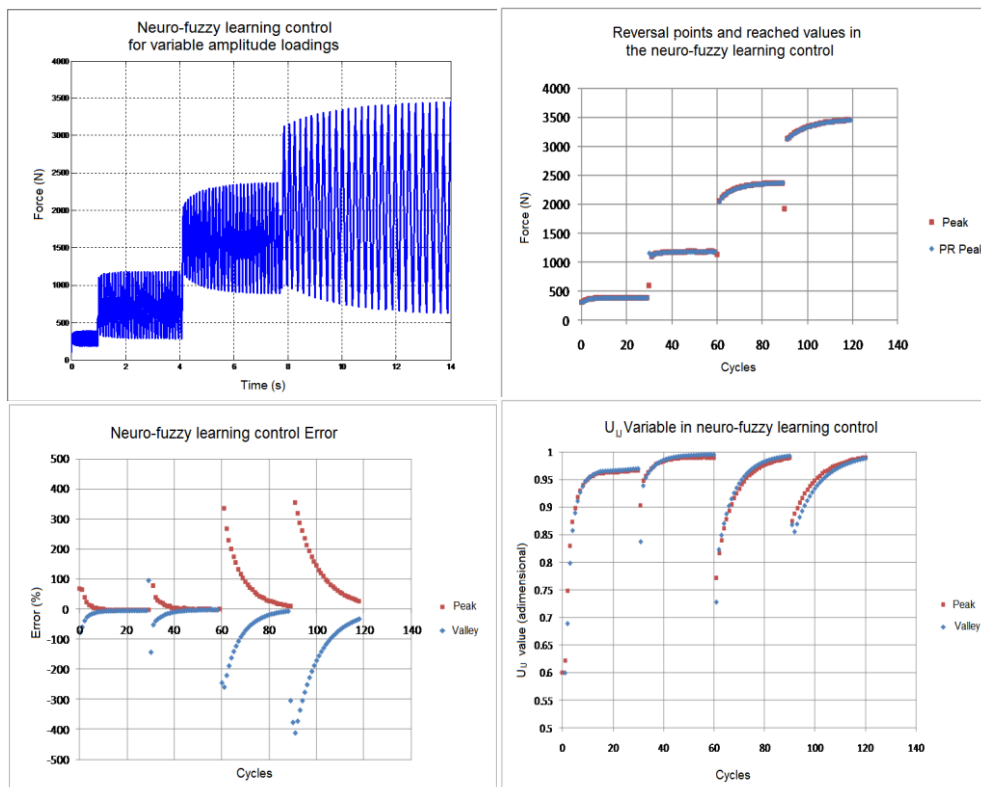Figure 6. Simulation of behavior of neuro-fuzzy learning control for constant amplitude loading {3500-1000}N

Figure 7. Simulation of behavior of neuro-fuzzy learning control for variable amplitude loading {400-200-1200-300-2400-800-3400-600}N

In Figure 6 it has been requested to the neuro-fuzzy learning control system a load of constant amplitude with peak value of 3500 N and valley equal to 1000 N. As it can be seen in the graph, the initial reversal value, which is set by software, is 0,50. After each cycle, the system learns and finds the optimal value of reversal in which the peaks and valleys requested are achieved which relative errors less than 0,01%. The load frequency achieved in the simulations was of 2,6 Hz. Figure 7 shows the result for a variable amplitude loading, simulating the behavior of the system subject to the loading history {400-200-1200-300-2400-800-3400-600}N, showing a good performance.

5. EXPERIMENTAL RESULTS

The pneumatic system was built in the Fatigue Laboratory of PUC-Rio. A structure of aluminum anodized was utilized (AlMgSi 0,5 F25) as presented in the Figure 8. The muscle is a pneumatic artificial muscle made by the FESTO model MAS-40-120N-MC-AA-K capable of generating a maximum force of 4 kN and an initial length of 120 mm. The load cell was chosen on the maximum generation capacity of muscle strength, and opted for a MK-Control load cell with ± 5kN of reading capacity. The valve control used is 3/2 single solenoid type FESTO, MHE4-MS1H-3/2G-QS-8 model that can work with pressure values of -0,9 to 8 bar, giving a maximum flow rate of 400 l/min, activated by an electric voltage of $24V_{dc}$ with a time of connection/disconnection of 3,5ms.

A 5 liter reservoir, whose purpose is to ensure the air supply to the muscle, was added to the system; to regulate the maximum air pressure a filter and a pressure regulator were added. Figure 8 shows the pneumatic system mounted in vertical configuration, with the small possible length of hose to avoid pressure drops. Beside the components submitted, the system has two claws for holding the specimen, one claws is a universal joint, whose purpose is to compensate any possible misalignment. A module for reading strain gages (NI 9237) is used to read the force generated by the muscle, and the solenoid valve is triggered by the analog module NI 9263, whose signal is amplified in both voltage and current by a power circuit. The system is controlled through a program developed in LabVIEW for the human-machine interface.
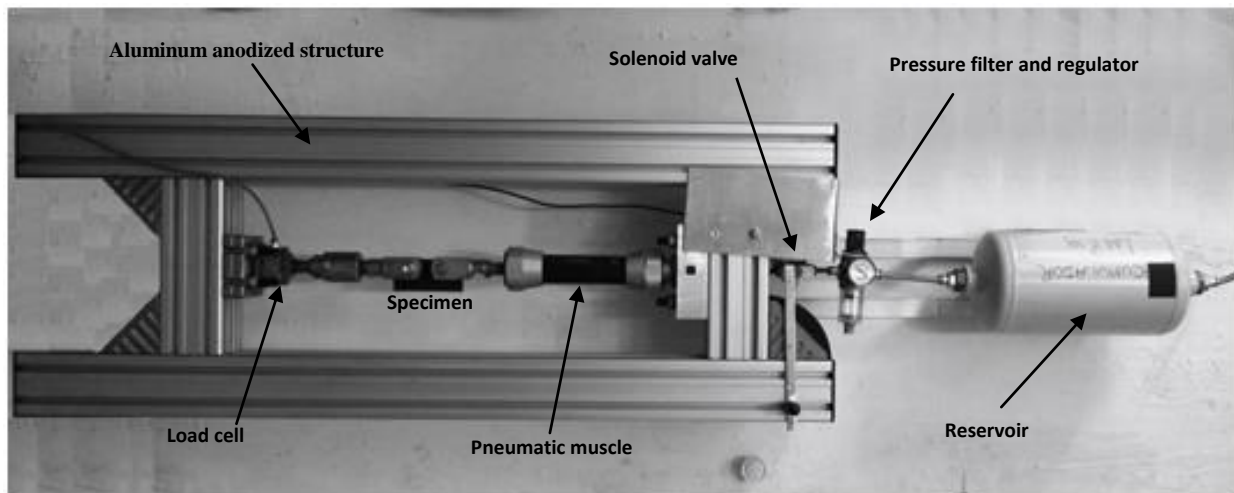

Figure 8. Pneumatic system for fatigue test

With the purpose of knowing the limits of work frequency (see Figure 9) in which the system could generate loads, was activated the solenoid valve with a pulse train with values of 0 (off valve) to 10V (on valve). For this, it was implemented in LabVIEW software through a signal generator, varying the values of frequency and duty cycle to achieve the desired amplitude levels. It was found that the smaller the amplitude. Time control signal ON is much shorter than the time control of signal OFF (approximately $t_{on}=1/9 \ t_{off}$ value). From the results shown in the Figure 9 can be observed that the muscle pressure increase, the frequency range increase for a given applied load. It can be shown that to loads in the range of 500N to 100N in a maximum pressure (5 bar) the system can obtain work frequencies in the range of 18 to 60 Hz.

The results of the learning control for loading of variable and constant amplitude are shown in Figure 10. It is possible to see the performance of the learning control applied to the pneumatic system. In Figure 10 calls it a load event with a peak value of 3500 N and a valley value of 1000 N, the work frequency for his pair of loads was 5 Hz, after 36 cycles of learning, the system learning control can achieve great reversal points, to generate the desired loads with relative errors less than 0,1% of amplitude required.
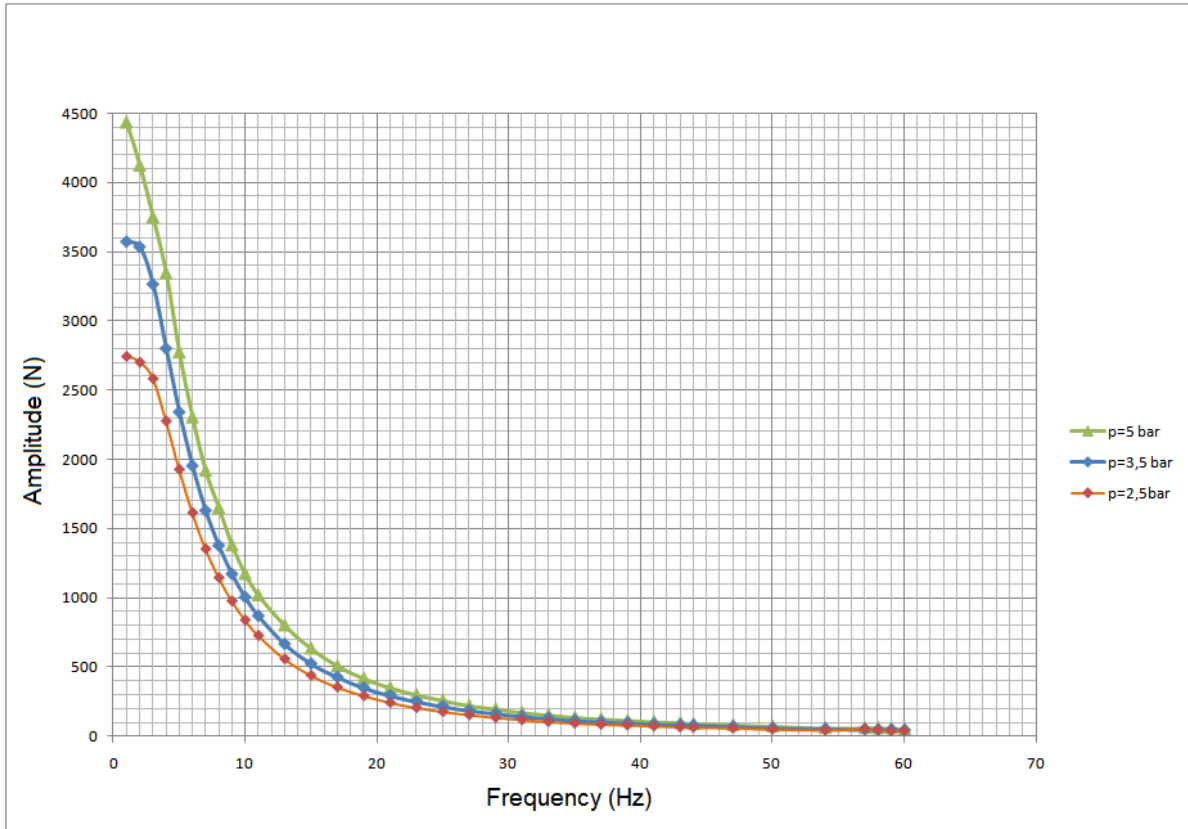
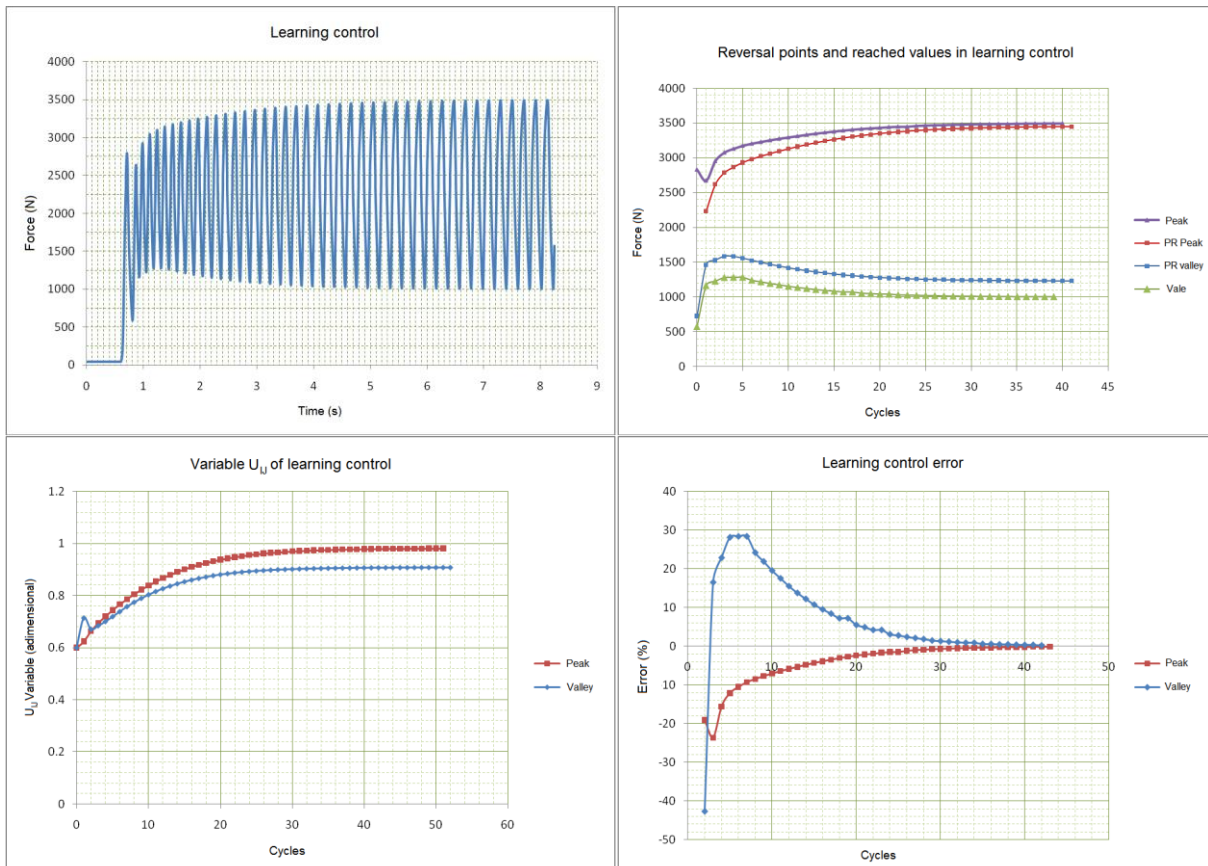Figure 9. Frequency response of the pneumatic system

Figure 10. Response of learning control for a constant amplitude load {3500-1000} N

The behavior of the learning control for variable amplitude loadings is shown in Fig. 11, where it can be seen how the system learning every pair of loads presented to the final converge to the desired value of peak and valley. It was considered an event of loading learned when the relative error of both loads (peak and valley) reached values lower than 0.1%, after that, we proceeded to present the next event for learning the same until you finish history of shipments. The work frequency changing according to the event presented.
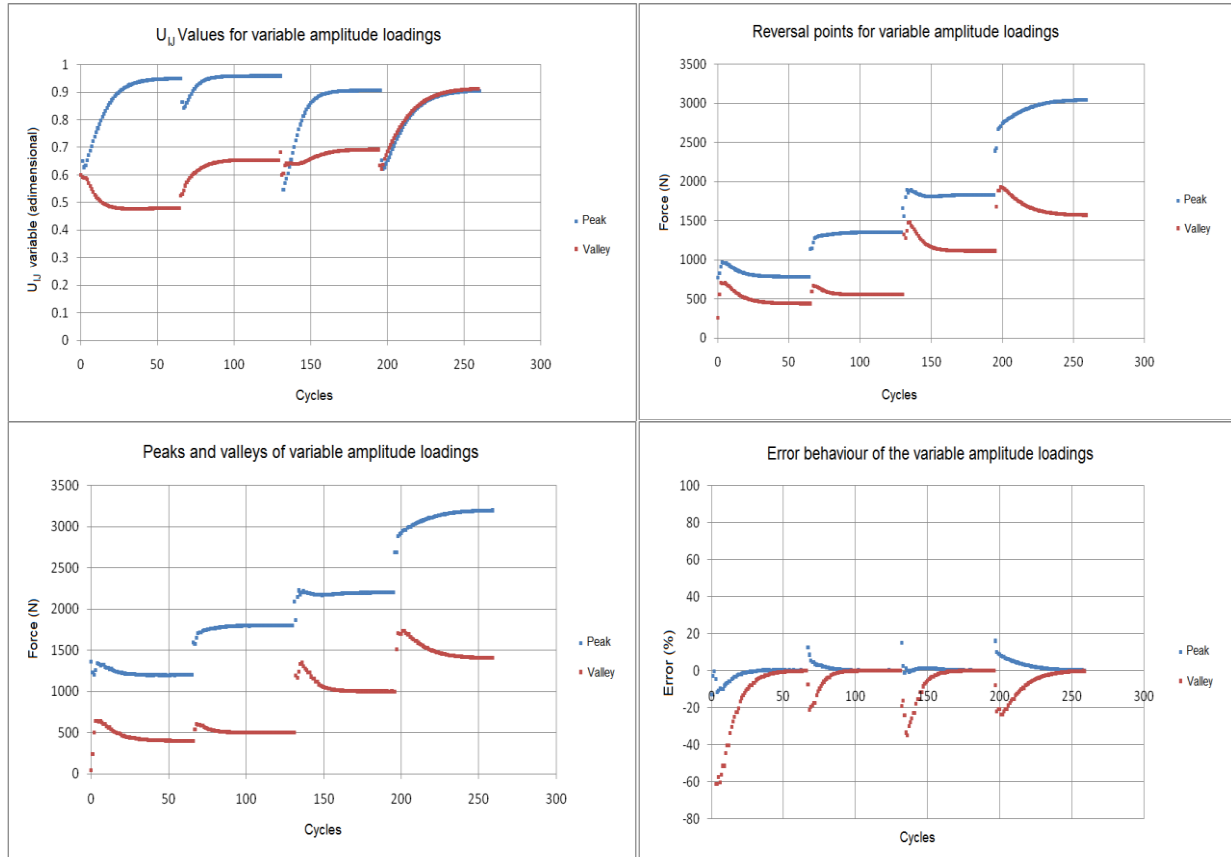

Figure 11. Response of learning control for a variable amplitude load

Neuro-fuzzy control tests were performed both for variable and constant amplitude loadings, resulting in satisfactory results. The dynamics of the pneumatic system showed a stable behavior for learning values less than 0,20 for all loadings, ensuring no overshoots. In Figure 12 a load of 3500 N (peak) and 1000 N (valley) was required in the beginning, while the value of the desired peak was reached after a few cycles of the learning process (Figure 12). The behavior of the neuro-fuzzy learning control to variable amplitude loads is presented in Figure 13, where for each value of peak and valley a relative error percentage lower than 0,1% was obtained after convergence.

6. CONCLUSIONS

An inexpensive pneumatic system for fatigue tests in tension with loads in the range of 0 to 4 kN was developed. The work frequency of the pneumatic system was limited by the time of inflation and deflation, characteristic of the pneumatic muscle. For values of required force between 400 and 4000N, the response of the control system was acceptable with relative errors less than 0,1%. For amplitudes lower than 400N, a delay between the level of real force and the level of measured force was detected. This was due to the time it takes to activate the solenoid valve (3,5 ms), increasing the errors to 1,4% for such lower amplitudes.
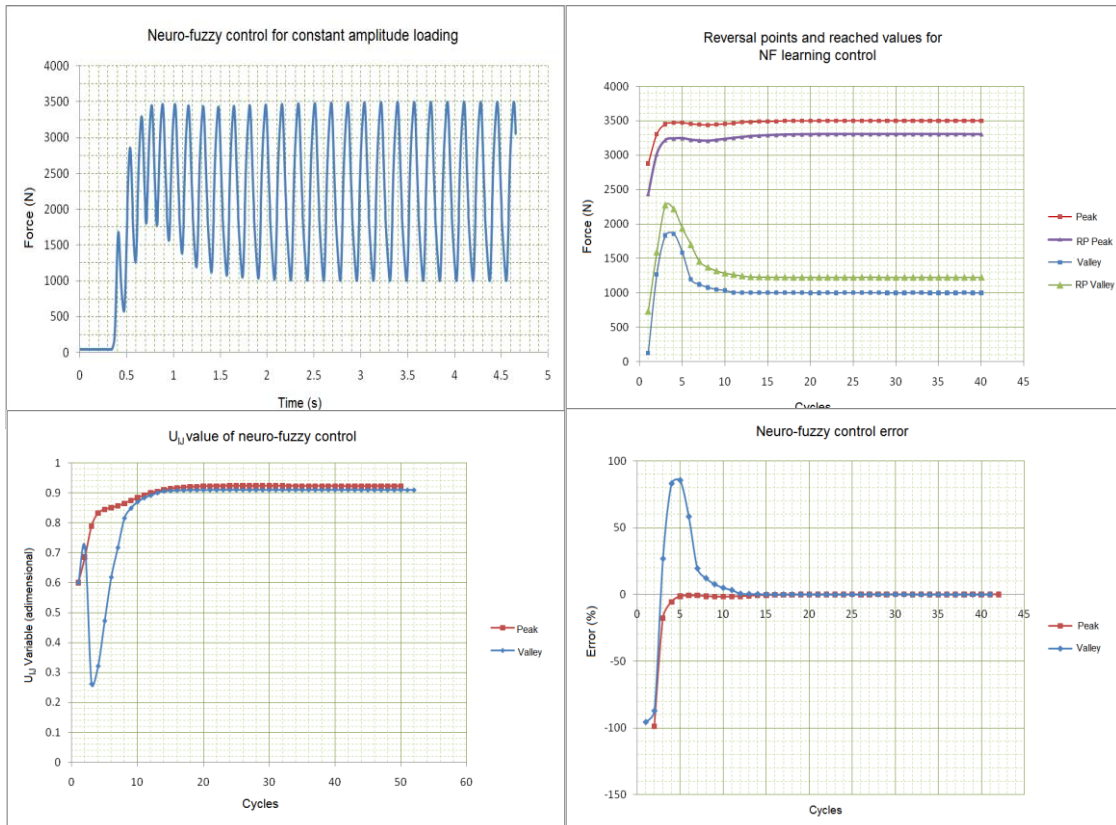
Figure 12. Response of neuro-fuzzy learning control for a constant amplitude load
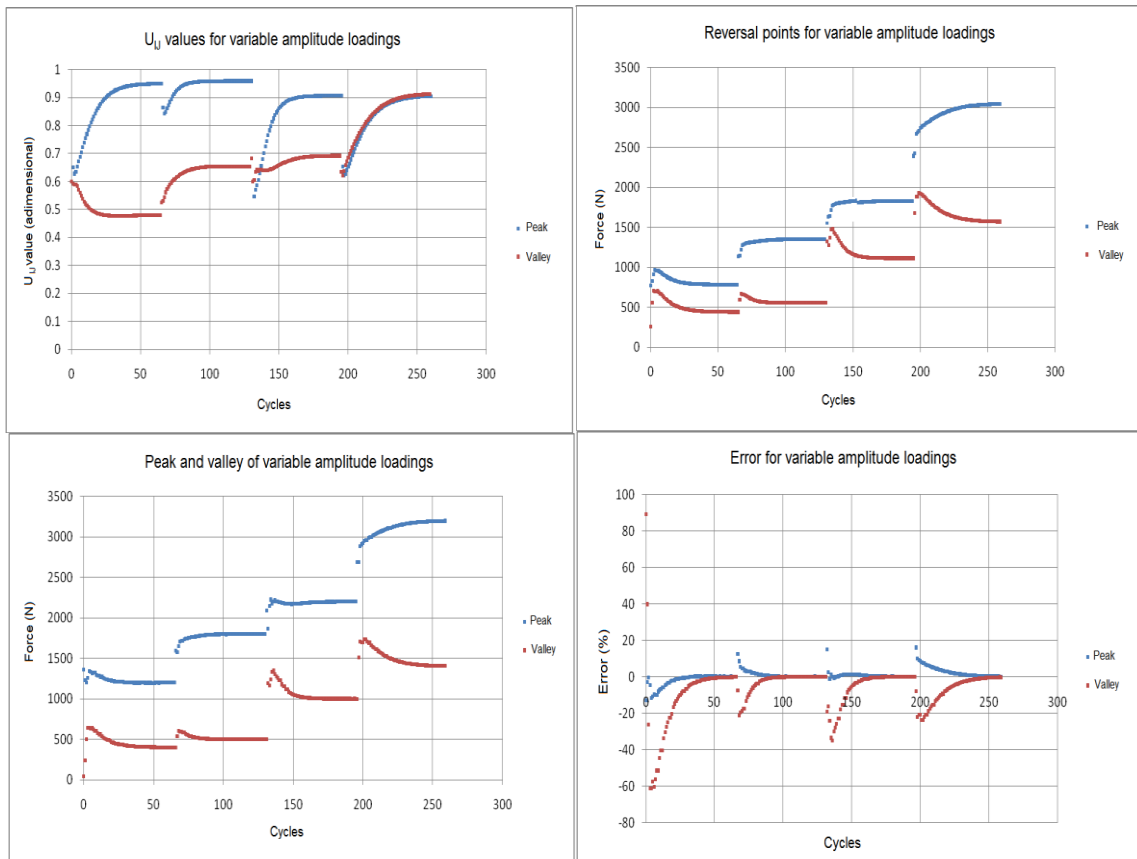

Figure 13. Behavior of neuro-fuzzy control system for variable amplitude loads

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